Prediction of Aggregate Multicomponent Time Series in Industrial Automated Systems Using Neural Network

A. Ragozin, V. Telezhkin, and P. Podkorytov

Abstract — **Today, Industry 4.0 merges the virtual reality and the real world generating new cyber-physical systems integrated into a single digital ecosystem. Such digital ecosystems which in their turn constitute complex automated systems require more efficient management solutions. The management process involves "anticipation" that means forecasting of an evolving event within the above systems at different (short-term, medium-term and long-term) time scales to develop and implement effective managerial influences. Data flows in the above industrial automated systems may be transformed into time series data to predict aggregate multicomponent time series data. Dynamic time series data within complex industrial automated systems result from interactions among multiple subsystems, and thus they are aggregate multicomponent time series. To generate the prediction, the task shall be divided into three steps. At the first step, the aggregate multicomponent time series shall be decomposed into several basic components (structural analysis of multicomponent time series) using the digital signal processing technology. This step involves digital spectrum analysis and digital signal filtering technologies. Second step is intended to generate a neural network architecture for generating a prediction according to the structure of the multicomponent time series being predicted. Third step involves the machine learning technology. Structural analysis of multicomponent time series and generation of a neural network architecture allow generating predictions at different time scales which is important for developing managerial decisions and influences within the industrial automated systems.**

Index Terms — **Neural Network, Time Series, Digital Filtering, Prediction, Automated System, Machine Learning, Industrial System, Multichannel Signal, Frequency Response.**

Prediction is one of key aspects of today's information technologies used to make decisions when implementing the management process in the industrial automated systems. The management process involves "anticipation" that means forecasting of an evolving event within the above systems to develop and implement effective managerial influences.

Manuscript received January 23, 2019; revised January 31, 2019.

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As the present-day (and future) industrial automated systems consist of multiple subsystems, all processes taking place in the above systems and indicated by the observed data flows are complex multicomponent processes. Data flows in the above industrial automated systems may be transformed into time series data to predict aggregate multicomponent time series data at different (short-term, medium-term and long-term) time scales.

Structural analysis of multicomponent time series and generation of a scalable prediction are required for forecasting at different time scales.

Russian [1–10] and foreign authors [11–23] have studied different issues of process modeling and forecasting in multiple technical systems.

The analysis of Russian and foreign studies shows that the issue of generation of a scalable prediction for multiple time intervals basing on observed aggregate multicomponent time series is still open. This paper focuses on steps and results of prediction of multicomponent time series.

Figure 1 shows an example of a complex signal (time series data) indicating a processes taking place in the technical system.

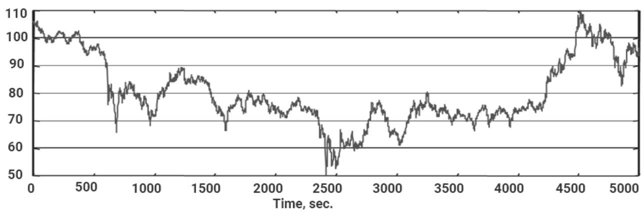

Fig. 1. Time series data used to generate a prediction.

At the first step of time series prediction (Fig. 1), the aggregate multicomponent time series is decomposed into several basic components (i. e. structural analysis of multicomponent time series) using the digital signal processing technology.

Digital signal processing is a flexible tool intended for preliminary preparation of data. According to the proposed method, for the purpose of preliminary digital processing of the time series being predicted, the signal passes through the low-pass filters (LPFs) comb generating a set of filtered components of the initial signal at the output. By a "vertical signal", we shall mean a set of signal components at the output of LPFs comb. Vertical signal is a multichannel signal at the output of LPFs comb consisting of, in this example, 55 FIR LPFs (finite impulse response (FIR) LPFs) with sequentially decreasing cutoff frequencies of their frequency response. This approach implies decomposition of the initial signal and subsequent noise filtering using a parallel set of digital LPFs. Figure 2 shows the result of initial signal conversion using the digital filtering method.

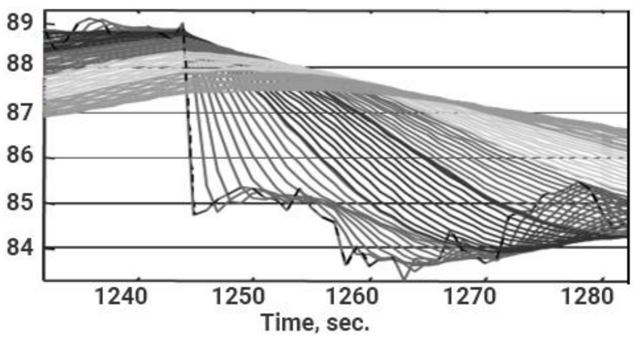

Fig. 2. Result of initial signal component conversion (The figure shows a part of the converted signal).

Multiple filtered signal components shown in Figure 2 are grouped into five bands (in this example) marked with different colors.

Figure 3 shows the other part of the initial signal (Figure 1) featuring a center line of each band.

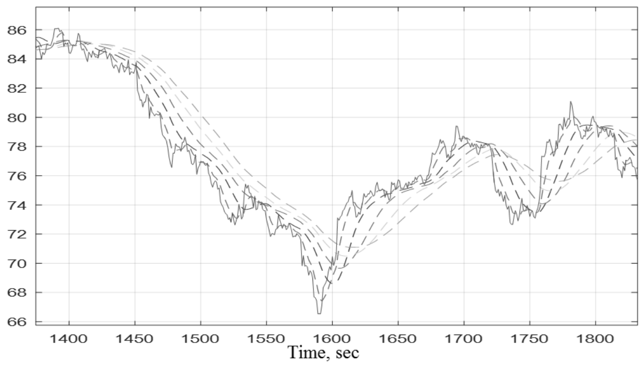

Fig. 3. Part of initial signal (Figure 1). The figure shows a center line of each band.

Therefore, Figure 3 shows the result of conversion of a section of the initial complex signal (Figure 1) into the enlarged multichannel signal (five channels or bands) consisting of five components — center lines of five bands (Figure 2). Each of five components (center lines) also has its band edges in the form of a standard deviation (SD) from the center line (not shown in Figure 3).

Figure 3 shows the result of the first step — structural analysis of multicomponent time series using the digital signal processing technology to decompose the aggregate multicomponent time series into several basic components (in this example, five basic band components).

Figure 4 shows the result of the second step — generation of a neural network architecture for generating a prediction according to the structure of the multicomponent time series being predicted. In this example, a neural architecture consisting of five neural networks was selected.

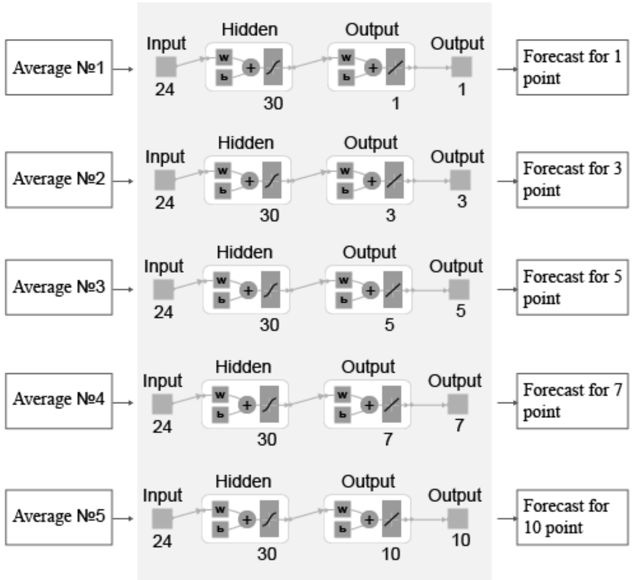

Fig. 4. Neural network architecture for forecasting five-component signal.

Several basic components (in this example, five basic band components, Figures 2 and 3) resulting from the structural analysis of multicomponent time series have different dynamic time response. “Slower and inertial” band components allow for a longer-term prediction over a longer time interval ahead as a result of a more extensive autocorrelation. Five predictions with different time horizons are generated for each of five band components based on their dynamic response using the neural network architecture (Figure 4) and machine learning technology.

The above five predictions with different time horizons are used to generate a final scalable prediction over different time intervals (i. e. prediction of the initial multicomponent time series). The most distant forecasting horizon of the initial multicomponent time series corresponds to the slowest band component. Its maximum band width is the sum of band widths of all components. The closest forecasting horizon of the initial multicomponent time series is defined by the parameters of the fastest band component (band average and width).

Figure 5 shows an example of a final scalable prediction of the initial multicomponent time series.

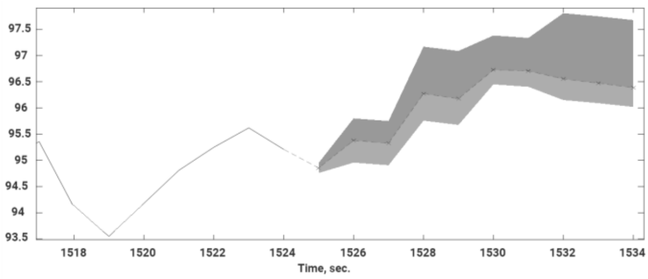

Fig. 5. Example of a final scalable prediction of the initial multicomponent time series.

The forecasting method used in this study and prediction of the initial multicomponent time series at different time scales generated using the above method contribute to effective managerial decisions and influences in complex industrial automated systems.

ISBN: 978-988-14048-5-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

REFERENCES

[1] M. S. Molotkov and A. K. Novikov, "Evolutionary Approach to Neural Network Setup and Learning," *Molodoy Uchyony*, no. 10 (114), pp. 69–71, May 2016.

[2] I. Yu. Alekseyeva, "Improvement of Reliability of Electrical Power Systems Based on Neural Technologies," *Electrotechnical Systems and Complexes*, no. 3 (32), pp. 15–19, 2016.

[3] I. S. Kobersi and V. V. Shadrina, "Energy Consumption Management Using Neural Networks," *Izvestiya SFedU. Engineering sciences*, no. 7 (84), pp. 190–195.

[4] V. N. Zuyeva and D. A. Trukhan, "Regression Methods for Forecasting Load Curve of Electric Equipment of Enterprises, Organizations and Institutions: Monograph," *Kuban State Technological University*. Krasnodar: KubSTU, 2017, pp. 123–135.

[5] A. P. Shuravin and S. V. Vologdin, "Filtering of Neural Network Input Data Using Digital Signal Processing Technology," *Bulletin of Kalashnikov ISTU*, no. 4, pp. 104–109, 2017.

[6] A. M. Abdurakhmanov, M. V. Volodin, E. Yu. Zybin, and V. N. Ryabchenko, "Methods for Energy Consumption Forecasting in Distributive Networks (Overview)," *Russian Internet Journal of Electrical Engineering*, pp. 3–23, 2016.

[7] D. T. Yakupov and O. N. Rozhko, "Artificial Neural Networks Perspective Application for Forecasting Cargo Carriage Volumes in Transportation Systems," *Statistical and mathematical methods in economics*, no. 5, pp. 49–58, 2017.

[8] Yu. N. Katsyuba and L. V. Grigoryeva, "ANN Application for Forecasting Technical Condition of Products," *International Research Journal*, no. 3 (45), pp. 19–21, 2016.

[9] A. N. Ragozin and E. A. Petryakov, "Forecasting of Economic Time Series Using Adaptive Autoregression Model," *Scientific and Analytical Economic Journal*, no. 1 (2), pp. 25-28, 2016.

[10] F. Murtagh, J.-L. Starck, and O. Renaud, "On Neuro-Wavelet Modeling," *Decision Support Systems Journal*, no. 37, pp. 475-484, 2004.

[11] K. Nikola, "DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and Its Application for Time-Series Prediction," *IEEE Transactions on Fuzzy Systems*, vol. 10, no. 2, pp. 144-154, 2002.

[12] S. Tomonobu and T. Hitoshi, "One-hour-ahead load forecasting using neural network," *IEEE Transactions on Power Systems*, no. 1, pp. 21–24, 2002.

[13] R. Huang, T. Huang, and Gadh, "Solar Generation Prediction using the ARMA Model in a Laboratory-level Micro-grid," in *IEEE Third International Conference on Smart Grid Communications*, Sydney, 2012, pp. 528–533.

[14] K. Pichotta and R. J. Mooney. (2016). Learning Statistical Scripts with LSTM Recurrent Neural Networks. *AAAI*. pp. 2800–2806. Available: https://pdfs.semanticscholar.org/1ceb/038d8b4838120e0dc0a11c949d032cebf5dd.pdf.

[15] N. Tax, I. Verenich, M. L. Rosa, and M. Dumas. (2017, May). Predictive Business Process Monitoring with LSTM Neural Networks. *arXiv.org*. Available: https://arxiv.org/pdf/1612.02130.pdf.

[16] M. Granroth-Wilding and S. Clark, "What Happens Next? Event Prediction Using a Compositional Neural Network Model," *AAAI*, pp. 2727–2733, 2016.

[17] F. Murtagh, J.-L. Starck, and O. Renaud, "On Neuro-Wavelet Modeling," *Decision Support Systems Journal*, no. 37, pp. 475–484, 2004.

[18] N. Singh, "Stochastic modeling of aggregates and products of variable failure rates," *IEEE Transactions on Reliability*, vol. 44, no. 2, pp. 279–284, 1995.

[19] W. E. Rhoden, "Observation of electromigration at low temperature," *IEEE Transactions on Reliability*, vol. 40, no. 5, pp. 524–530, 1991.

[20] R. M. Geffhen, J. G. Ryan, and G. J. Slusser, "Contact Metallurgy Development for VLSI Logic," *IBM Journal of Research & Development*, vol. 31, no. 6, pp. 608–616, 1987.

[21] F. Fantini, C. Morandi, "Failure modes and mechanisms for VLSI ICs – a review," *IEEE Proceedings*, vol. 132, no. 3, pp. 74–81. 1985.

ISBN: 978-988-14048-5-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)